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Abstract

Economic geography has offered several insights to understand the role of geography in shaping creativity, innovation and the way they are connected in space. Unfortunately, most attention has been devoted to analyzing cities and urban regions as the ideal context where creativity and innovation come together. Emerging counter-narratives are challenging this urban perspective and proposing that creativity-led innovation can also thrive in rural, often more peripheral, places. Theoretically, different arguments have been proposed, yet a clear conceptualization is lacking. We propose to link these arguments to two complementary ways in which creativity-led innovation might be at play, either as innovation in creative industries or as creative workers contributing to innovation across industries. Methodologically, most evidence comes from intriguing case studies and country-specific surveys, yet comparative quantitative evidence is missing or misleading. In this study, we propose to use trademarks as an alternative indicator to patents, better fitting creativity-led innovation.

We illustrate the opportunities from our conceptualization and measurement with a comparative study of European regions. Using a database combining large scale occupational data with patent and trademark activity for the period 2011-2019, we analyze the relationship between creative occupations and innovation activity in rural regions. Our findings suggest that creativity-led innovation processes operate in rural regions but can only be uncovered when using trademarks as innovation indicators. These findings bear key policy implications, as they inform efforts towards formulating and monitoring the role of creativity and innovation for rural contexts.

Keywords: creativity, innovation, regions, rural, urban, creative occupations, patents, trademarks

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INTRODUCTION

When it comes to innovation, a clear insight from decades of research on regional innovation systems (Asheim and Hansen, 2009), and territorial innovation models (Capello and Lenzi, 2013) is that regions not only differ in the extent to which they innovate but also in how they innovate. Next to science-based and technology-driven regional innovation specializations, creativity-led innovation is one of the ways in which local firms might come up with novel ideas, products and processes and generate economic value (Marques and Morgan, 2021, Breznitz, 2021). Economic geography has focused on how geography matters, for creativity, for innovation and for the link between creativity and innovation (Feldman, 1994). The basic intuition is that creativity and innovation do not develop in isolation from the spaces and contexts where the individuals and organizations generating new ideas operate, live and socialize.

Most studies have stressed how cities and the related urban contexts appear the ideal hotbed for creativity-led innovation activities (Florida et al., 2017). On the one hand, creative talent is drawn to cities because of the infrastructures, amenities and cultural openness that they offer (Florida, 2004). On the other hand, cities offer excellent opportunities for connecting both diverse and specialized activities (Bettencourt et al., 2007; Balland et al., 2020). The two mechanisms appear to reinforce each other and point to creativity and innovation concentrating in cities, especially large ones.

This urban perspective has increasingly been challenged, both conceptually and empirically. Emerging narratives suggest that rural, often more peripheral, regions have been neglected when it comes to both creativity and innovation (Wojan and Nichols, 2018; Eder, 2019). Unfortunately, these emerging narratives tend to rely on case studies or national surveys and comparative empirical work is missing. Overall, we lack a clear picture of how creativity-led innovation might offer a systematic pattern of innovation in rural regions. In this study we aim at advancing our understanding by proposing a conceptualization of creativity-led innovation that combines a creative industry and creative occupation perspective. In a nutshell, creativity-led innovation can be both about specific innovation types emerging in creative industries but also about creative workers helping to define the value of innovation in specific innovation phases, across all industries. We then link the two perspectives to the theoretical arguments emerging from the literature and to the methodological challenges of measuring creativity-led innovation. Herein, we argue that trademarks appear as a more fitting innovation indicator than patents.

We illustrate the opportunities from our conceptualization and measurement approach with a comparative study of European regions. We investigate the relationship between regional shares of employment in creative occupations and innovation activity for the period 2011-2019. Our findings suggest that creativity-led innovation processes are at play in rural regions, but only appear when using trademark-based indicators instead of patent-based ones.

Our results can inform policy: it remains difficult to measure the contribution of creativity beyond urban contexts, yet smart specialization strategies for these regions could benefit from insights on how to reveal innovation trajectories that exploit the presence of creative activities (Castaldi & Drivas, 2023). For many rural regions such local strengths are clearly not residing in the technological or scientific domain but can be found in a broader set of territorial assets and small firm capabilities (Radosevic, 2018). Hence, mobilizing metrics of creativity and innovation that span a broader range of activities than those focused on high-tech specializations or on creative industries only is bound to do more justice to what happens in rural regions.

RESEARCH BACKGROUND

Conceptualizing creativity-led innovation

The literature on how creativity matters for innovation is extensive. We aim here at synthesizing and connecting two main conceptual foci that can be recognized in recent research. A first perspective relates to research on creative industries and their specific innovation types, a second perspective concerns how creative occupations contribute to innovation across all industries.

As for the first perspective, a stream of concepts has been developed to capture the specific types of innovation generated within creative industries. These include concepts such as soft innovation (Stoneman, 2010), aesthetic innovation Eisenman, 2013), stylistic innovation (Cappetta et al., 2010), symbolic knowledge innovation (Kesidou et al., 2024) and many more. The main purpose was to stress how innovation could be defined in terms of new non-functional or non-technical elements, with learning happening in the space of symbolic knowledge rather than synthetic or analytical (Asheim and Hansen, 2010).

Yet, the above concepts have increasingly found application beyond the creative industries, in line with the acknowledgement that creativity has a role to play across industries, embodied in the creative occupations to be found there too. This second perspective includes investigations of the role of creatives in the downstream phases of innovation processes (Ravasi et al., 2012), with reference to the importance of a persuasive value proposition for successful innovation diffusion (Mendonca, 2014). Other studies have highlighted symbolic knowledge learning in valuation dynamics (Davids and Frenken, 2018) or have looked at creative input as a way to upgrade product positions (van Tuijl and Carvalho, 2014).

Table 1 summarizes the two dimensions of conceptual work helping to understand creativity-led innovation. This two-dimensional conceptualization does not specify how geography matters. In fact, the role of geography for creativity-led innovation has also been studied extensively. Yet, it is fair to say that most studies, either focusing on creative industries or on creative occupations, have celebrated cities as ideal sites (Florida, 2004, Grabher, 2004, Vinodrai, 2006). We are not denying here the powerful forces that urban agglomerations play for creativity-led innovation. Instead, our goal is to look for arguments why creativity-led innovation might also thrive in rural regions, using the conceptualization proposed here as a frame of reference.

Table 1: Two-dimensional conceptualization of creativity-led innovation

Dimension	Key concepts	Key perspectives
Creative industries generate novelty in specific ways	Soft innovation, aesthetic innovation, stylistic innovation, symbolic knowledge innovation, and more	Mostly a ***creative industry*** perspective, focus on specific ***innovation types***
Creatives help to define the symbolic value of innovation	Role of creatives in downstream phases of innovation, in upgrading of products, in valuation dynamics	Mostly a ***creative occupation*** perspective, focus on specific ***innovation phases***

Beyond the city: creativity and innovation in rural regions

A first strand of research started challenging Florida's notion that the creative class was mostly to be found in cities. A few scholars suggested that creative talent was not only attracted to cities but might also turn to rural areas for natural amenities like outdoor activities and clean air (McGranahan et al., 2011). Relatedly, small cities have also been found to be places where creative talent might migrate to, thanks to affordable housing, high quality of life and tight-knit communities (Waitt & Gibson, 2009). A few scholars leveraged the notion of 'rural artistic havens' and documented their existence in selected countries (Wojan et al., 2007). Others talked about a 'creativity-led rural renaissance' (Argent et al., 2013). This line of research has stressed how rural communities can offer a cultural environment where artists and creative talent thrive (Sorensen, 2009). The cultural assets in rural regions can also allow developing whole industries and clusters of creative activities (Power & Collins, 2021).

A second strand of research is the literature on 'innovation in the periphery' (Eder, 2019). This literature has challenged the urban narrative on innovation (Shearmur, 2012) and characterized peripheries across several dimensions (Glückler et al., 2023). In a geographical sense, peripheries often correspond to low-density, remote and rural regions (Pugh & Dubois, 2021). Eder & Trippl (2019) have summarized several properties that can constitute strengths of peripheral regions when it comes to innovation. A seminal argument was given by Shearmur (2015), who coined the notion of slow innovators: these are innovative small firms that do not depend on frequent interactions with other economic actors, nor rely on information whose value critically decays with time. These innovators are likely to avoid high-density areas where there are more opportunities but also more risks of knowledge spillovers. These arguments align with work that has found that low-density areas tend to specialize rather than diversify (Caragliu et al., 2016), with a focus on internally developed innovation capabilities that benefit from loyalty-based employment relations (Isaksen & Karlsen, 2016). The related innovation is less about being at the global technological frontier and more about optimizing processes and products with incremental, new-to-the-firm innovation thanks to internal capabilities accumulated over time (Petrov, 2012; Shrolec et al., 2021; Azzoni & Tessarin, 2024). At the same time, global market leader firms might also operate in low-density rural regions. Fritsch & Wywich (2021a) provided evidence for Germany that successful innovative firms can be found 'in the middle of nowhere'. From the perspective of creative individuals, the remoteness of peripheries might offer protected sites for experimentation and unconventional agency (Grabher, 2018). Glückler (2014) captured this argument with the notion of 'controversial innovation', novel ideas that challenge the norm and are more likely to emerge in the periphery. Finally, distance from the core might come with institutional leeway and opportunities for specific policy support for economic activities (Meili & Shearmur, 2019).

A third strand of research is more recent and somewhat scattered. It focuses specifically on how creativity-led innovation can emerge in rural regions, which is also the specific focus of our study. This pattern of territorial innovation represents an alternative to science-based or technology-driven innovation specializations (Asheim & Hansen, 2009; Capello and Lenzi, 2013). One traditional argument is that rural regions can build on 'soft' territorial assets for entrepreneurship and innovation (Pires et al., 2014; Galetti et al., 2021; Stefan et al., 2021; Azzoni & Tessarin, 2024). Distinctive assets like heritage, history or local culture can be brought into local products whose authenticity is closely related to their geographical origins (Castaldi & Mendonca, 2024). Herein, creatives can help articulate the symbolic and cultural value of place-based assets when developing innovation, in line with the second dimension of our conceptualization of creativity-led innovation.

A different argument emerges from the innovation in the periphery literature: the marginality and remoteness of rural regions might be particularly conducive to innovation in creative and cultural fields, where experimentation and opposition to dominant paradigms can be key (Grabher, 2018; Kesidou et al., 2024). This argument supports the first dimension of our conceptualization of creativity-led innovation.

Table 2 summarizes the key arguments put forward by these emerging, 'beyond the city' narratives. When it comes to considering the empirical evidence supporting the different arguments, one has to conclude that it is often based on case studies and systematic comparative evidence is scattered (Argent et al., 2013; Eder, 2019). Hence, we turn to the methodological challenges that have stood in the way of producing further evidence to inform the ongoing debate.

Table 2: Key theoretical arguments from the three main research strands on rural innovation.

Focus of research	**Theoretical arguments**
Rural regions as artistic havens	Rural regions as artistic havens and places of cultural heritage (Wojan et al., 2007, Eder and Trippl, 2019), supporting the development of local creative industries (Power and Collins, 2021). Creatives are also attracted to natural amenities (McGranahan et al., 2011) and tight-knit communities (Waitt and Gibson, 2009).
Innovation in the periphery	Slow innovators thrive in peripheries (Shearmur, 2015) and low-density areas focus on specialization and developing internal innovation capabilities (Caragliu et al., 2016), benefitting from loyalty-based employment relations (Isaksen and Karlsen, 2016). Peripheries offer sites for experimentation and 'controversial innovation' (Glückler, 2014), acting as protected environment for unconventional agency. Distance from the core comes with institutional leeway and opportunities for specific policy support for economic activities (Meili & Shearmur, 2019)
Creativity-led innovation in rural regions	Creativity and regional soft assets as sources of ***rural innovation***, where ***creatives*** extract symbolic value from place-based assets (Wojan & Nichols, 2008, Stefan et al., 2021). Marginality and distance favor truly radical alternatives (Grabher, 2018) and ***symbolic knowledge innovation*** (Kesidou et al., 2024) in ***creative industries.***

Revealing creativity-led innovation in rural regions: evidence and methodological challenges

The theories discussed above have been inspired and informed by intriguing empirical case studies of selected rural regions. Those case studies have been able to elucidate underlying mechanisms and processes behind the emergence of creativity-led innovation in rural regions (Grabher, 2018; Kesidou et al., 2024). At the same time, it remains unclear whether the cases are 'exceptions that prove the rule' or are instead indicative of systematic patterns that might be found across different types of rural regions. In his literature review Eder (2019) concludes that 'findings from case studies should not be transferred uncritically to other regions' (p.134). This caveat warns against giving false hopes to regions that might consider replicating the success stories of other rural regions only to realize that those cases were unique. In this sense, it seems critical to accumulate more empirical evidence by conducting comparative work. Before outlining our own approach, we briefly discuss prior efforts in this direction.

There is survey-based evidence coming from different national surveys. Innovation surveys offer key advantages for capturing innovation and its processes. Lee & Rodríguez-Pose (2014) exploited data from the UK Annual Small Business Survey. They studied the relationship between creativity and innovation by implementing both an industry and an occupational approach and concluded that the latter allows to better reveal the contribution of creative activities to innovation. Their findings provided evidence that creative industries tended to be more innovative in urban contexts, but innovation leveraging creative workers did not happen more often in cities than it did in rural areas. Complementary evidence for England also comes from the studies by Phillipson et al. (2019) and Tiwasing et al. (2023), reporting comparable or even higher levels of innovative activity in rural than urban areas. For the United States, Wojan & Nichols (2018) leveraged a survey focused on rural innovation: their findings indicate a positive contribution of design to rural innovation. For Europe as a whole, Capello and Lenzi (2013) used the Community Innovation Survey and complementary data to map territorial innovation patterns of which two correspond to creativity-led innovation: smart and creative diversification and imitative innovation, both characterizing several rural regions in Europe. At the same time, it is clear that relying on surveys has limitations. They tend to focus on single countries and given years, hence timely comparative work is challenging. Also, representation of firms from low-density areas might be challenging in surveys even when they aim to be representative for the whole national population of firms (Davies et al., 2012). Approaches using combinations of secondary data available from public sources are promising. For instance, Sleuwaegen & Boiardi (2014) have used indicators from the European Innovation Scoreboard to analyze the link between creativity and regional innovation. Unfortunately, their analysis does not provide specific insights on rural innovation.

Using intellectual property rights data to measure innovation overcomes some of the limitations of survey data. It allows timely and consistent analysis and enables comparative work between countries and regions (Hall and Jaffe, 2018, Mendonça et al., 2004). Of course, this data also comes with its own limitations, which are well-known. Some of the limitations particularly apply to instances when only one intellectual property right (IPR) is used. In fact, patents have by far been the favorite innovation proxy in economic geography (Fritsch & Wyrwich, 2021b; Rodríguez-Pose & Lee, 2020). Wojan & Nichols (2018) and others have suggested that patents might have an urban bias hence might fail to reveal innovation in rural regions. To complicate matters, studies of creativity-led innovation using patents as innovation indicator have mostly focused on cities or metropolitan areas as geographical units. There is an emerging understanding that combining IPRs can allow a broader take on regional innovation (Castaldi & Mendonça, 2022; Ribeiro et al., 2022) and help to capture innovation across more types of regions (Pinate et al., 2023; Roper & Jibril, 2023).

Given our two-dimensional conceptualization of creativity-led innovation, two features of trademark data appear of particular interest. First, trademarks have the potential to measure innovation in creative industries better than patents, which instead work best for technology-based contexts (Stoneman, 2010, Ribeiro et al., 2022). This has both to do with the fact they are distinctive symbols closely connected to symbolic knowledge production (Castaldi, 2018) and with the absence of technical novelty requirements for trademark registration. Second, trademarks are filed in relation to the market introduction of new products, hence they capture downstream innovation phases (design, marketing, commercialization) better than patents (Mendonça et al., 2004). Gatrell and Ceh (2003) explain how trademarks can in fact capture 'corporate creativity' as crucial input for the successful market introduction and positioning of new products. Many activities happening in these downstream innovation phases have to do with tasks that engage creative workers, including designers, product developers, artists, in making the innovation attractive, persuasive and resonant with potential customer's wishes and needs (Mendonça, 2014). These relate strongly to tasks where symbolic knowledge is the key knowledge base developed (Asheim & Hansen, 2009).

As for the role of geography, both patents and trademarks tend to concentrate in large cities (Castaldi, 2024). Yet, trademark data has features that indicate it might offer opportunities to better capture some of the features of firms in rural regions. Trademarks often indicate incremental, new-to-the-firm innovation and innovation by small and medium-sized firms (Morales et al., 2024). It should be noted that large firms also make extensive use of trademarks, but small firms use them relatively more than patents (Helmers and Rogers, 2010). Last but not least, emerging evidence on the geography of patenting and trademarking suggests that they tell different stories, with large cities often concentrating both activities and secondary cities focusing on either one (Castaldi, 2024).

Table 3: Key features of patents vs trademarks as innovation metrics, in bold the dimensions most relevant for our conceptualization

	Patents	**Trademarks**
Subject matter	Novel technological inventions	Distinctive symbols
Main legal requirements for registration	Novelty Industrial applicability	Distinctiveness (Intention to) Use in market
Innovation phases	Research Development	Product Development/Design Marketing/Commercialization
Innovation types	New-to-the-world technical invention	Product/service innovation, non-technological/soft innovation, new-to-the-firm innovation
Knowledge base	Analytical/Synthetic knowledge	Symbolic knowledge
Occupations	Technical/engineering	Creative/design
Industries	Mostly high-tech sectors	All industries, including creative industries
Type of firms	Mostly large firms	All firm sizes, including SMEs
Geography	Concentrated in large cities and secondary cities focusing on technology	Concentrated in large cities and secondary cities also focusing beyond technology

Table 3 summarizes the key features of patents and trademarks as complementary innovation indicators. When considering innovation phases and types, but also knowledge bases in relation to occupations and industries, the link to the two dimensions of creativity-led innovation, as presented in Table 1, is much more evident for trademarks than for patents. Still, using trademarks to measure innovation may lead to false positives (Hall and Jaffe, 2018), because trademarks can also be filed for pure marketing purposes, like brand modernization or extension (Block et al., 2014). Instead patents may have less false positives, because they are checked for novelty. They rather suffer from false negatives since they only capture technology-based innovation. In fact, the picture is more nuanced than what the above expectations suggest. Morales et al. (2024) is the only study providing comparative evidence from samples of innovations: they found that false positives are there also for patents, since many patented inventions never make it to widespread adoption or commercialization, and false negatives also for trademarks. This is also the case for the creative industries, where many firms do not even trademark (Castaldi, 2018). The relative strength of trademarks vs patents depends on several factors, including industry, firm type and innovation type (Morales et al., 2024).

Given the discussion above, we propose that the relationship between creativity and innovation at the regional level can best be studied by capturing the regional share of employment in creative occupations and by combining patents and trademarks as innovation indicators. Next, we detail our research design and empirical strategy.

EMPIRICAL RESEARCH DESIGN

Data sources

We compiled an original panel dataset of European regions to empirically investigate the relationship between creative occupations and regional innovation.

We obtained data from Eurostat on occupations from the Labour Force Survey (LFS), a collection of national household surveys conducted across Europe. This database includes information on individuals indicating occupation (by ISCO-08, 3-digit level) and place of work (by NUTS level 2), among many other variables.

In our work, we take a regional perspective, conducting the analysis at the NUTS-2 regional level (the most disaggregated level at which occupational data are available at the 3-digit level) in the period between 2011 and 2019. The start of the period comes from data availability, as occupational data following the latest ISCO classification (2008 version) is only available from 2011. The end of the period is chosen both to avoid the pandemic years and to take into account grant lags for patent and trademark applications.

In the database development process, we had to deal with differences in the level of aggregation and coverage of LFS data across the EU. We dropped Bulgaria, Malta, and Slovenia from the analysis as these countries did not report occupation data at the 3-digit level. Differently, for the Netherlands, the data is only available at country level, so we opted for keeping the whole country and classifying it entirely as a single urban region. For the United Kingdom, occupation data was only available for regions at the 1-digit NUTS level, that is for a total of 12 NUTS regions. We also removed observations without occupational or regional identification and workers from regions outside European Union countries (such as candidate countries like Türkiye or other countries where workers commute to work). These actions resulted in removing only 4% of the workers. The final dataset covers 16.2 million workers for the period 2011 to 2019.

We obtained patent filings at the European Patent Office from the OECD REGPAT Database (August 2022 edition) and trademark filings at the European Union Intellectual Property Office (EUIPO) from the ISI-Trademark Data Collection (ISI-TM) (Neuhäusler et al., 2021). In both cases, filings are supra-national ones, while companies can also file at national offices. Yet, the link between new trademarks and innovation appears stronger for EUIPO filings than national ones (Flikkema et al., 2019), which helps to validate our measure.

To assign patents to regions, we use the information of the location of the inventors, which is closest to the location where the invention was developed. Trademark records only include the location of the owner. For small and medium-sized companies the two locations typically coincide, while for large companies they may not. This means that trademarks can overestimate innovation for regions hosting headquarters of large companies, often capital regions (Castaldi, 2024). At the same time, those business functions where creative workers mostly operate, like design, product development and marketing, tend to concentrate in the headquarter location of companies, making the bias concerns less salient for our analysis.

Patent data from REGPAT was already geocoded, instead we had to geocode and regionalize trademark data starting from the owner address. We dropped 5.5% of the data because of missing information in the owner address field. For both patents and trademarks, we counted only applications that made it to registration, but used the application year as reference since it is closest to the actual moment that the innovation was developed. In case patents or trademarks had inventors or owners in different regions we opted for whole counting, hence counted that patent or trademark for all regions.

The other indicators used as controls, as well as employed persons, were collected from Eurostat. In total, our data covers 29 European countries (24 EU countries, 4 EFTA and the UK) and 247 NUTS regions, accounting for 234 NUTS-2 regions, plus 12 UK NUTS-1 regions and 1 region for The Netherlands.

Definition of key variables

We used yearly counts of new patents and trademarks to measure regional innovation. We count trademarks registered in all market classes, both in classes associated with creative industries (to capture the first dimension of creativity-led innovation, e.g. a trademark associated with a new fashion line) and in other classes (to capture the second dimension, e.g. a trademark associated with a high end technological product). Ó hUallacháin & Douma (2021) suggested that a fair comparison of cities or regions of different size should rely on using relative instead of absolute counts of innovations. Hence our dependent variables capture patent and trademark intensities, defined as the number of patents or trademark per thousand employed persons. Using employment instead of population aligns with the idea that we are mostly capturing corporate creativity (Gatrell & Ceh, 2003).

As for measuring creative activities, early studies focused on identifying creative industries (Cunningham, 2013). At the same time, it has become clear that an industry approach understates the actual contribution of creative activities. Creative talent is also employed in non-creative industries, hence a focus on creative occupations helps to systematically map creative activities in firms across all sectors (Higgs & Cunningham, 2008; Markusen et al., 2008; Lee & Rodríguez-Pose, 2014). We followed recent studies and defined creative occupations as those classified as creative and cultural by Eurostat, based on 4-digit ISCO codes (Eurostat, 2018) (see for instance, Bakhshi, Freeman & Higgs, 2013; Rodríguez-Pose & Lee, 2020; OECD, 2022). Not all 4-digit occupations within a given 3-digit ISCO code might count as creative, but the LFS data is only at the 3-digit level. Table A.1 lists all 3-digit ISCO codes that we count as creative. We indicate with an asterisk (*) those 4-digit occupations that Eurostat would not classify as creative or cultural (Eurostat, 2018; OECD, 2022). It is worth noting that national statistical offices do not always align in terms of classifications, hence some extra codes were added in specific countries (OECD, 2022). However, due to the scarcity of data on 4-digit occupations, most studies follow the same strategy and adopt the complete composition of 3-digit ISCO codes to define cultural and creative occupations (Higgs & Cunningham, 2008; Sleuwaegen & Boiardi, 2014). Overall, the chosen 3-digit occupation codes represented in 2019 4.25% of the total occupations in the 29 European countries considered. This selection of occupations aligns with a more restrictive notion of creative workers than the very broad initial take on the creative class used in early studies like Boschma & Fritsch (2009).

Another crucial step for the analysis consisted in classifying regions by levels of urbanization. We follow Eurostat, which classifies NUTS-3 regions based upon criteria of geographical contiguity and minimum population in an area (Eurostat, 2021). Since our data is at the NUTS-2 level, we had to aggregate NUTS-3 areas to the NUTS 2 regional level. We used the distribution of employed persons in each NUTS-3 to classify NUTS-2 regions as urban, intermediate or rural (see Figure 1). This employment-based aggregation offers important advantages over approaches based on total population or population density. In particular, it accounts for the economically active segment of the population (excluding elderly and children). This is especially pertinent in rural areas, which often experience population ageing and youth outmigration. By focusing on employed persons rather than total population, our method more accurately captures the labor market realities of rural regions and avoids distortions introduced by demographic imbalances unrelated to economic activity.

Methods of analysis

Our interest lies in testing the significance of the relationship between creativity and innovation at the regional level. We leveraged the panel data structure of our data and estimated a two-way fixed-effect model by year and region, which allows to reveal factors that are not already explained by region-specific or year-specific characteristics.

The dependent variable represents regional *innovation* measured either by patent or trademark intensity, calculated as patents or trademarks per 1000 employees. We took the logarithmic of the intensity since the distribution across regions is highly skewed. Given that intensity can also be zero, we used the logarithmic transformation ln(intensity+1). $Innovation_{rt}$ is then either $Ln\ patents\_employ_{rt}$ or $Ln\ trademarks\_employ_{rt}$.

Our main independent variable of theoretical interest is the share of creative occupations (*Creative_sh*), defined as the percentage of all occupations in the focal region and year.

The baseline specification of our regressions is as follows:

$$Innovation_{rt} = \beta_1 + \beta_2\, Creative\_sh_{rt-1} + \beta_3\, HumanCapital\_sh_{rt-1} + \beta_4\, SmallSize\_sh_{rt-1} + \beta_5\, High\_tech\_service\_sh_{rt-1} + \beta_6\, High\_tech\_manuf\_sh_{rt-1} + \varphi_r + \sigma_t + \varepsilon_{rt}$$

The model includes several independent variables to control for factors that are often found to affect regional innovation. We control for human capital as the share of population (from 25 to 64 years) with tertiary education (*HumanCapital_sh*). We do so since earlier studies have questioned whether the effect of creative activities is not simply driven by human capital intensity (Boschma & Fritsch, 2009; Marrocu & Paci, 2012). We also control for the firm size composition of the region, taking the percentage of workers employed in firms with less than ten employees (*SmallSize_sh*). Finally, we control for productive structure by including the regional shares of employment in knowledge-intensive services (*High_tech_service_sh*) and high and in medium-high tech manufacturing (*High_tech_manuf_sh*). Prior studies have shown that patent and trademark intensity at the regional level depend on both the firm size and sectoral composition of regions, as size and sector influence the propensity of firms to register patents and trademarks (Pinate et al., 2023).

All control variables are time-lagged by one period in the model estimations, to take into account the lag between generating creative ideas and turning them into patent or trademark applications. This also partly controls for endogeneity concerns, which we will deal more in detail in the robustness checks analysis.

RESULTS

Descriptive results

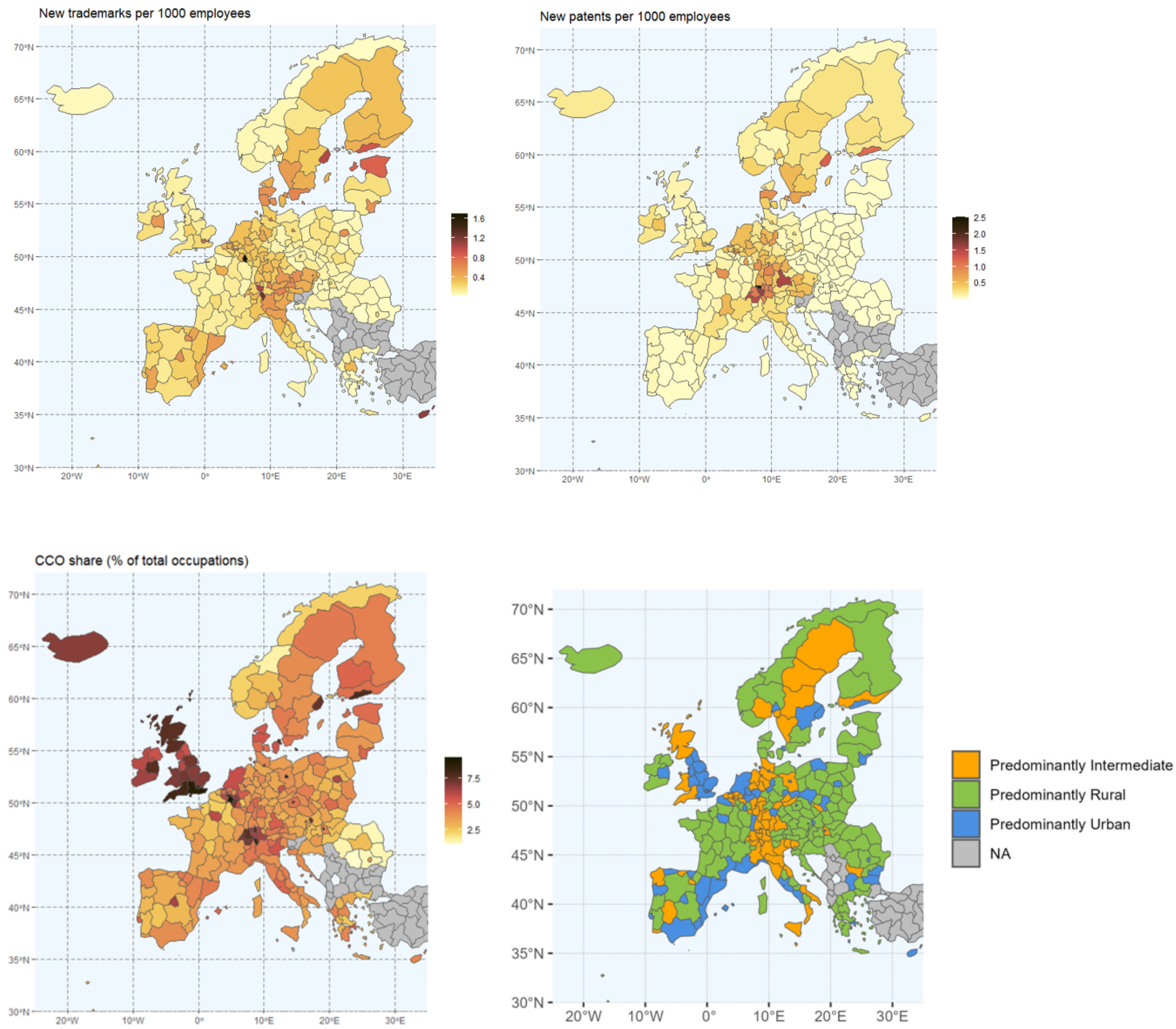
Figure 1 shows maps for the distribution of our key variables of theoretical interest for all 247 NUTS 2 regions. The first and second map show patent and trademark intensity; the third map illustrates the share of CCOs relative to total employment, the fourth displays how regions are classified as urban/intermediate/rural.

As expected, patent activity appears much more concentrated spatially than trademark activity. This result aligns with other studies that have found different regional distributions of these two measures of innovation in Europe (Pinate et al., 2023, Castaldi & Drivas, 2023). The maps clearly indicate regions that score similarly on the two innovation indicators but also several regions that score differently.

The map displaying the shares of creative occupations shows that some regions clearly specialize in these activities. Regions in the United Kingdom, Ireland, and Iceland stand out with the highest shares, along with regions in Switzerland, Belgium and Northern Italy. One can recognize several regions that have been characterized as pursuing ‘creative application’ innovation patterns (Capello & Lenzi, 2013).

Table 4 reports the descriptive statistics of the main variables, while the correlation tables can be found in the appendix (Table A.2). Figure 2 shows the scatterplots of rural and urban regions with respect to the main relationship of interest. The plots for trademark intensity show a positive correlation with shares of creative occupations for both types of regions. The clouds of observations also reveal that both variables have higher average values for urban than for rural regions, yet their association is comparable. The plot for patents also suggest a positive relationship, but somewhat flatter. Next, we assess these relationships in a multivariate setting.

Figure 1: Trademark and patent intensity, share of creative occupations and urban/intermediate/rural classification for all regions in our sample, in 2019

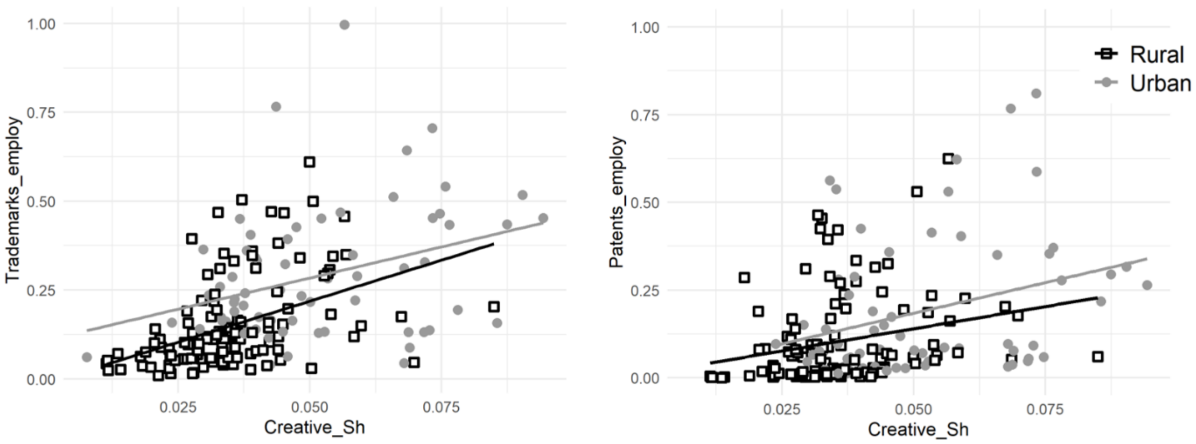


Note: data for the Netherlands at country level, the UK at NUTS 1 and all others at NUTS 2.

Table 4: Overview of variables, including definition, data sources and descriptive statistics

Variables	Definition	n	mean	stdev	median	min	max	Data source
Patents_employ	Patents per 1,000 employed persons	2121	0.239	0.352	0.103	0.000	2.817	OECD REGPAT and Eurostat
Trademarks_employ	Trademarks per 1,000 employed persons	2180	0.226	0.221	0.167	0.001	2.326	EUIPO and Eurostat
Creative_sh	Share of creative occupations	1941	0.043	0.017	0.039	0.008	0.109	LFS
HumanCapital_sh	Share of population aged 25-64 with tertiary education	2158	0.282	0.094	0.274	0.090	0.584	Eurostat
SmallSize_sh	Share of occupations in companies with less than 10 employees	1941	0.236	0.098	0.218	0.000	0.678	LFS
High_tech_service_sh	Knowledge-intensive high-tech services share of employment	1927	0.025	0.015	0.021	0.005	0.096	Eurostat
High_tech_manuf_sh	High and medium-high manufacturing share of employment	1992	0.059	0.037	0.050	0.002	0.220	Eurostat

Figure 2: Scatterplot of rural and urban regions, capturing the correlation between share of creative occupations and patents and trademark intensity



Regression results

Table 5 reports results for the baseline model estimated using all regional observations. The findings point to a significant positive relationship between the share of creative occupations and trademark intensity. This confirms the general idea that there is a link between creativity and the innovation phases and types captured by trademarks. Instead, the relationship with technological innovation as measured by patents is not statistically significant. This result stands notwithstanding the positive and significant correlation between creative occupations and patenting in the correlation analysis (Table A.2). Exploiting the within-region variation over time in the fixed effects model, we rule out the effect of time-invariant characteristics (e.g. agglomeration externalities (Carlino and Kerr 2014) which may be driving the correlation between creative occupations and patenting in the simple correlation analysis. The main results are there also after including the control variables in the models. Of these controls, regional human capital also plays a significant role, but it does not take away the significance of creative occupations as specific human capital.

Table 5: Baseline results – all regions

	Ln_patents_employ		Ln_trademarks_employ	
	(1)	(2)	(3)	(4)
lag_Creative_sh	-0.154	-0.150	0.654***	0.723***
	(0.097)	(0.117)	(0.120)	(0.140)
lag_HumanCapital_sh		0.141***		0.259***
		(0.049)		(0.058)
lag_SmallSize_sh		0.019		0.036
		(0.024)		(0.028)
lag_High_tech_service_sh		0.002		0.220
		(0.246)		(0.294)
lag_High_tech_manuf_sh		-0.015		-0.191
		(0.134)		(0.157)
Observations	1,865	1,675	1,914	1,680
R^2	0.986	0.986	0.955	0.960
Adjusted R^2	0.984	0.984	0.948	0.953
Residual Std. Error	0.028	0.028	0.035	0.034
Region FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes

Note: Coefficients are significant at *p < 0.10; **p < 0.05; ***p < 0.01 level. Standard error in parentheses.

We then estimated the same models for rural regions only (see Table 6). The findings indicate no statistically significant association between creative occupations and innovation when innovation is measured with patents. Instead, a significant positive association is there when regional innovation is measured with trademarks. These results align with the overall results in Table 5. The results for the control variables indicate that innovation captured by trademarks is more likely to be associated to innovation by small and medium sized firms (Flikkema et al., 2014, Morales et al., 2024), service innovation (Schmoch, 2003) or non-technological innovation (Mendonça et al., 2004).

Table 6: Model results for rural regions

	Ln_patents_employ		Ln_trademarks_employ	
	(1)	(2)	(3)	(4)
lag_Creative_sh	-0.185*	-0.223	0.694***	0.886***
	(0.106)	(0.151)	(0.148)	(0.198)
lag_HumanCapital_sh		0.115**		0.126
		(0.059)		(0.077)
lag_SmallSize_sh		0.017		0.079*
		(0.033)		(0.043)
lag_High_tech_service_sh		0.132		0.878*
		(0.349)		(0.455)
lag_High_tech_manuf_sh		-0.195		-0.366*
		(0.150)		(0.191)
Observations	881	713	921	718
R^2	0.968	0.970	0.921	0.935
Adjusted R^2	0.962	0.965	0.908	0.923
Residual Std. Error	0.024	0.024	0.033	0.032
Region FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes

Note: Coefficients are significant at *p < 0.10; **p < 0.05; ***p < 0.01 level. Standard error in parentheses.

For reference, we also estimate our models for urban regions only, see Table 7. The results broadly align with those for all regions. Yet, we do note that the human capital variable behaves differently in these models, as compared to those for rural regions. For urban regions, human capital is not associated to patenting, but it is for trademarking. A highly educated population, together with the presence of creative workers, helps to explain trademark intensity. For rural regions, human capital does instead play a significant role to explain patent intensity, while there is no link to trademark intensity.

Table 7: Model results for urban regions

	Ln_patents_employ		Ln_trademarks_employ	
	(1)	(2)	(3)	(4)
lag_Creative_sh	0.129	0.041	0.539**	0.457*
	(0.192)	(0.211)	(0.230)	(0.239)
lag_HumanCapital_sh		0.034		0.466***
		(0.105)		(0.119)
lag_SmallSize_sh		-0.078		-0.026
		(0.050)		(0.056)
lag_High_tech_service_sh		-0.410		0.134
		(0.402)		(0.457)
lag_High_tech_manuf_sh		0.323		0.381
		(0.330)		(0.375)
Observations	507	502	515	502
R^2	0.985	0.985	0.965	0.973
Adjusted R^2	0.982	0.983	0.960	0.968
Residual Std. Error	0.029	0.029	0.036	0.032
Region FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes

Note: Coefficients are significant at *p < 0.10; **p < 0.05; ***p < 0.01 level. Standard error in parentheses.

Robustness checks

A first robustness check considers the possible urban bias in the measurement of innovation, in particular when using patents. The insignificant results for the models explaining patent intensity may be due to an underestimation of intensity due to an overestimation of the denominator when one considers employment or population (Wojan, 2022). This estimation bias could affect the models explaining regional trademark intensity too. Dotzel & Wojan (2022) suggest using as denominator an ‘inventive class’ which takes into account the regional workforce that can directly contribute to innovation. Doing so ensures that one does not confound regional composition effects with productivity effects (Wojan, 2022) and is eventually able to assess the specific contribution of groups of workers, creative ones in our case. The inventive class proposed by Dotzel & Wojan (2022) encompasses Science, Engineering, and Technical workforce categories and other 11 occupations. This robustness check might be particularly relevant for rural regions, which may suffer most from an employment composition bias. Tables 8, 9 and 10 report the results.

Table 8: Results when using innovation intensities relative to inventive class employment - all regions

	Ln_patents_inventive		Ln_trademarks_inventive	
	(1)	(2)	(3)	(4)
lag_Creative_sh	-0.625*	-0.458	2.133***	1.827***
	(0.319)	(0.355)	(0.481)	(0.485)
lag_HumanCapital_sh		-0.014		0.211
		(0.148)		(0.202)
lag_SmallSize_sh		0.165**		0.185*
		(0.072)		(0.098)
lag_High_tech_service_sh		-0.319		0.058
		(0.748)		(1.020)
lag_High_tech_manuf_sh		-0.158		-0.797
		(0.407)		(0.545)
Region FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	1,865	1,675	1,913	1,680
R^2	0.980	0.983	0.927	0.949
Adjusted R^2	0.977	0.980	0.916	0.941
Residual Std. Error	0.092	0.086	0.141	0.117

Note: Coefficients are significant at *p < 0.10; **p < 0.05; ***p < 0.01 level. Standard error in parentheses.

Table 9: Model results when using innovation counts relative to inventive class employment - rural regions

	Ln_patents_inventive		Ln_trademarks_inventive	
	(1)	(2)	(3)	(4)
lag_Creative_sh	-0.694	-0.675	2.569***	2.815***
	(0.428)	(0.522)	(0.662)	(0.779)
lag_HumanCapital_sh		-0.121		-0.181
		(0.202)		(0.301)
lag_SmallSize_sh		0.162		0.328*
		(0.113)		(0.168)
lag_High_tech_service_sh		-0.126		1.538
		(1.202)		(1.787)
lag_High_tech_manuf_sh		-0.416		-1.481**
		(0.516)		(0.751)
Region FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	881	713	921	718
R^2	0.964	0.975	0.900	0.929
Adjusted R^2	0.958	0.970	0.884	0.916
Residual Std. Error	0.096	0.084	0.150	0.125

Note: Coefficients are significant at *p < 0.10; **p < 0.05; ***p < 0.01 level. Standard error in parentheses.

Table 10: Results when using innovation counts relative to inventive class employment - urban regions

	Ln_patents_inventive		Ln_trademarks_inventive	
	(1)	(2)	(3)	(4)
lag_Creative_sh	0.160	0.203	2.177**	0.706
	(0.563)	(0.623)	(0.889)	(0.762)
lag_HumanCapital_sh		-0.286		0.745**
		(0.309)		(0.379)
lag_SmallSize_sh		-0.031		-0.083
		(0.146)		(0.179)
lag_High_tech_service_sh		-0.402		0.487
		(1.189)		(1.455)
lag_High_tech_manuf_sh		0.472		0.059
		(0.976)		(1.194)
Region FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	507	502	514	502
R^2	0.979	0.980	0.928	0.961
Adjusted R^2	0.976	0.976	0.917	0.954
Residual Std. Error	0.084	0.084	0.140	0.103

Note: Coefficients are significant at *p < 0.10; **p < 0.05; ***p < 0.01 level. Standard error in parentheses.

The findings are largely in line with our baseline results. Even accounting for employment composition, the share of creative occupations is not significantly related to patent intensity, while the relation to trademark intensity remains, also for rural regions. This confirms our intuition that trademarks are better at capturing the contribution of creative occupations, in line with our conceptualization of creativity-led innovation.

Our second robustness check instead tackles the endogeneity issues that we briefly mention earlier and that are common in regional analysis of innovation. Whereas the inclusion of regional fixed effects and different control variables in our model reduce concerns of capturing spurious relations, endogeneity may still affect our findings (Angrist & Pischke, 2009; Wooldridge, 2014). A first issue pertains to reverse causality, possibly emerging if the successful registration of a trademark would lead to hiring more creatives workers. The use of time-lagged regressors and the fact that trademarks tend to be associated to improvements in financial performance rather than employment growth, at least in the short term (Helmers & Rogers, 2010) possibly reduce worries for reverse causality. A second concern relates to a possible omitted variable bias, whereby the share of creative could turn to be positively associated to innovation only through an omitted variable. This could happen if, for example, the more open-minded culture of a region (Florida, 2004) or the presence of heritage (Castaldi and Mendonça, 2024) would foster innovation instead of the specific availability of creative workforce. Regional fixed effects already take care of these issues and indeed they help to explain a significant share of regional variation. Lastly, the results may be affected by measurement errors (e.g. if the Labor Force Survey sampling was biased towards creative occupations in innovative regions). Considering the challenge of measuring overall creativity available in the region and the fact we have to rely on data on formal employment, a possible concern is that our measures underestimate actual creatives as we miss out on self-employed, creative side jobs and hobbyists.

To address these endogeneity concerns, we resort to an instrumental variable approach. Our identification strategy relies on historical data and a shift-share approach widely used in the economic geography literature (Bartik, 1991; Goldsmith-Pinkham et al., 2020). The main intuition behind our instrument is that the presence of creative occupations in area might be explained by an history of outstanding creatives and innovators (Cosci et al., 2022). Building on this idea, we leverage the so-called Pantheon database (Yu et al., 2016), which contains information on the life and main occupation of 'famous' individuals, extracted from Wikipedia pages. Despite limitations (see the discussion in Laouenan et al., 2022), the database offers original historical data which is not bound to administrative data sources. We compute the share of famous people in creative occupations born in each region over the total number of famous people born in the region (see Appendix B for details). Importantly, we focus only on famous people born in a given region from 1800 onwards and who passed away before the year 2000. Firstly, creative activities as we know them today are intimately connected to modern culture and emerged after the industrial revolution of the XIX century (Mayer, 2018; Moore, 2014). Secondly, we take 2000 as a cutoff for our instrumental variable to prevent creatives to possibly be involved in patenting or trademark activities. All in all, taking a period encompassing the 19th and 20th century allows to use the most relevant information yet exogenous information for our instrument. The intuition behind this instrument is that the presence of famous creatives in the past may be a factor explaining the presence of creative occupations in the region nowadays, for instance because of emulation, local tradition or specific cultural traits of the region. At the same time, the fact a relatively large share of famous creatives was born in an area should have no direct effect on the number of trademarks and patents filed today, since those creatives cannot have contributed any longer to local innovation activities.

Since we estimate panel data regressions, a time invariant instrument would not be enough to estimate the coefficients of interest. Therefore, we combine the information on the share of famous creatives (share part of the instrument) with the yearly share of creative occupations at the EU to provide the time variation to our instrument (shift part of the instrument). The time variation is then the same for all regions, hence the identification of the parameter exclusively comes from share component of the instrument (Goldsmith-Pinkham et al., 2020). In formal terms, our instrument is built as follows:

$$bc\_sh_{r,t} = \frac{Creative\ Influential\ Born_r}{Total\ Influential\ Born_r} * \frac{Creative\_occ_{EU,t}}{Total\_occ_{EU,t}}$$

where the first term captures the region-specific share element (share of famous creatives born in the region over the total famous individuals) and the second term captures the time-varying shift element based on EU-wide variation common to all regions.

Table 11 shows the results with the instrumental variable testing the association between shares of creative workers and trademark intensity only, since the results for patent intensity were statistically non-significant in the main models presented previously.

Table 11: Results for the IV models explaining regional trademark intensity – all regions, rural and urban regions

	IV - All regions	IV - Rural	IV - Urban
fit_lag_Creative_sh	2.960***	2.146*	2.525**
	(0.801)	(1.156)	(1.144)
lag_HumanCapital_sh	0.168**	0.079	0.321**
	(0.071)	(0.090)	(0.151)
lag_SmallSize_sh	0.217***	0.232	0.145
	(0.070)	(0.145)	(0.110)
lag_High_tech_service_sh	-0.283	0.539	-0.530
	(0.365)	(0.561)	(0.611)
lag_High_tech_manuf_sh	-0.309*	-0.377*	-0.073
	(0.176)	(0.198)	(0.475)
Num.Obs.	1680	718	502
R2 Adj.	0.945	0.918	0.963
R2 Within Adj.	-0.134	-0.014	-0.120
Region FE	X	X	X
Year FE	X	X	X
F-test 1st St.	53.77	19.65	23.12

Note: Coefficients are significant at *p < 0.10; **p < 0.05; ***p < 0.01 level. Standard error in parentheses.

The results indicate that the chosen instrumental variable is indeed relevant, with an F-test for the first stage of our 2SLS regressions being above the conventional level of 10. The coefficients for our IV in the first stage are also positive and significant (see Table B.2 in the appendix) suggesting that the share of famous creatives born in a region explains the current share of creative occupation. In terms of findings, the 2SLS estimations confirm the positive and significant relation between regional shares of creative workers and trademark intensity, with the size of the estimated coefficients being larger than those in baseline regressions and the coefficient for rural regions being now less significant than the one for urban regions. The difference in the coefficient size between baseline and 2SLS may be related to possible measurement error in our measure of creative activities, which implies a possible under-estimation of the number of creative occupations in our data.

DISCUSSION AND CONCLUSION

This study had the ambition to reveal creativity-led innovation in rural regions. Conceptually, we proposed to acknowledge the dual role that creativity can play for innovation, in defining a specific innovation type that characterizes creative industries and in articulating the symbolic value of innovation thanks to creative workers employed across industries. We argued that this dual conceptualization could also help to recognize and measure creativity-led innovation in rural regions.

The theoretical inspiration came from a diverse set of perspectives on creativity, innovation and rural regions. These perspectives are fueling a counternarrative that aims to offer an alternative to the dominant take that creativity-led innovation is a urban phenomenon. This counter-narrative has proposed intriguing arguments supported by fascinating cases, but comparative evidence has been lacking. We proposed trademark-based indicators of innovation that allow to better reveal creativity-led innovation in general, and in rural regions specifically.

Our findings show that regional innovation appears to be significantly positively related to the presence of creative workers. In particular, creativity-led innovation processes can thrive in rural regions too, next to urban regions. Yet, a positive association between creative occupations and innovation in rural regions was only there when innovation was measured with trademarks.

Our study has a number of limitations of which we are aware, some already discussed in the methods section. First, our geographical level of analysis captures relatively large regions which are likely to include places with different degrees of accessibility and population density (see Martinus et al., 2020 or Roper and Jibril, 2023).. Future research could venture into more spatial analyses, as already suggested by Shearmur (2011) and leverage geo-coded data to offer micro-geographical perspectives. That would require matching innovation data to firm-level data and their occupational counterparts. Those efforts could be done for single countries and could reveal underlying mechanisms that studies at the regional level cannot uncover. Alternatively, one could consider adding explanatory variables capturing inter-regional linkages or relational factors (Martinus, 2018).

Second, our empirical analysis focused on European rural regions, which might be endowed with heritage and soft assets more than rural regions elsewhere. This might matter for both dimensions of creativity-led innovation, as either offering fertile ground for creative industries or an attractive location for creative workers. A good deal of trademarks filed in European rural regions does reflect soft territorial assets. For instance, rural regions that stood out were Roskilde County (Denmark), Trentino-Alto Adige and Südtirol (Italy) and Upper Austria and Salzburg (Austria). These regions share a strong cultural and natural heritage and territorial identity. At the same time, our conceptualization does cover multiple ways in which creativity might matter, also in manufacturing or agriculture, probably less so in mining. Replication of our approach beyond the European context would be most helpful to understand the generalizability of our findings.

Third, IPR-based indicators of innovation have known limitations. In this study we counted all patents and trademarks as having the same probability of representing innovation and also the same value. Overall, it is fair to say that innovation indicators based on trademark data appear useful but their validity can be further established across industries and geographies. It would also be interesting to replicate our analysis with data generated with novel techniques, like those used in Nathan and Rosso (2022) or Dalhke et al. (2025). These techniques, together with ad-hoc surveys, might also help to reveal non-corporate innovation. For the specific case of rural regions, scholars have argued that creativity contributes to social innovation (Howaldt & Schwarz, 2010), often by non-corporate actors, such as civil society organizations, local associations, and community networks.

Despite these limitations, our study's findings provide original insights that bear relevance for researchers and policymakers alike. We have contributed novel quantitative comparative evidence on factors associated to rural innovation, thereby complementing the qualitative evidence from case studies of specific regions and specific cases of innovation in rural and peripheral regions. The latter evidence remains important to understand the underlying mechanisms. It should be noted that many empirical quantitative studies on the geography of creativity and innovation only include cities and urban regions as geographical units of analysis. The problem does not lie with the findings themselves: indeed, cities work well at bringing together creative workers and at offering a fruitful environment for innovation activities. What is instead problematic is then rushing to the conclusion that cities are the only geographical context for creativity-led innovation.

A key insight for policy is that monitoring regional innovation and smart specialization efforts cannot be done solely relying on patent metrics (see also Castaldi & Drivas, 2023, Castaldi and Mendonça, 2022). Such metrics work well at revealing creativity-led innovation efforts in urban contexts but are clearly problematic in case of rural contexts. The very spirit behind smart specialization policies is to promote investment in activities that represent local strengths and have potential for deployment in innovation and entrepreneurial activities (Foray et al., 2018). For many rural regions such local strengths are clearly not residing in the technological or scientific domain but can be found in a broader set of territorial assets and small firm capabilities (Radosevic, 2018). Hence, mobilizing metrics of creativity and innovation that span a broader range of activities than those focused on high-tech specialization is bound to do more justice to what happens in rural and peripheral regions. In this sense, such efforts can inform place-based approaches aiming at tapping into hidden potential of regions that often feel 'left behind' (Rodríguez-Pose, 2018). An important next question is of course whether rural creativity-led innovation modes also contribute to regional development instead of becoming the next instance of 'innovation without development' (Marques and Morgan, 2021). When tackling this question, it will be important to take a broad notion of regional development into account (Binz and Castaldi, 2024, Cortinovis et al., 2024), as creativity-led innovation might contribute less to economic growth but more to broad well-being.

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Appendices

Table A.1: List of the 3-digit ISCO-08 codes used to define cultural and creative occupations and the 4-digit codes they include. An asterisk (*) indicates those 4-digit occupations that Eurostat would not classify as creative or cultural (Eurostat, 2018; OECD, 2022) but are included in our list of 3-digit occupations.

ISCO-08	Cultural and creative occupations
216	Architects, planners, surveyors and designers
2161	Building architects
2162	Landscape architects
2163	Product and garment designers
2164	Town and traffic planners
2165	Cartographers and surveyors
2166	Graphic and multimedia designers
235	Other teaching professionals
2351*	Education methods specialists
2352*	Special needs teachers
2353	Other language teachers
2354	Other music teachers
2355	Other arts teachers
2356*	Information technology trainers
2359*	Teaching professionals n.e.c.
262	Librarians, archivists and curators
2621	Archivists and curators
2622	Librarians and related information professionals
264	Authors, journalists and linguists
2641	Authors and related writers
2642	Journalists
2643	Translators, interpreters and other linguists
265	Creative and performing artists
2651	Visual artists
2652	Musicians, singers and composers
2653	Dancers and choreographers
2654	Film, stage and related directors and producers
2655	Actors
2656	Announcers on radio, television and other media
2659	Creative and performing artists n.e.c.

ISCO-08	Cultural and creative occupations
343	Artistic, cultural and culinary associate professionals
3431	Photographers
3432	Interior designers and decorators
3433	Gallery, museum and library technicians
3434*	Chefs
3435	Other artistic and cultural associate professionals
352	Telecommunications and broadcasting technicians
3521	Broadcasting and audio-visual technicians
3522*	Telecommunications engineering technicians
441	Other clerical support workers
4411	Library clerks
4412*	Mail carriers and sorting clerks
4413*	Coding, proof-reading and related clerks
4414*	Scribes and related workers
4415*	Filing and copying clerks
4416*	Personnel clerks
4419*	Clerical support workers n.e.c.
731	Handicraft workers
7311	Precision-instrument makers and repairers
7312	Musical instrument makers and tuners
7313	Jewellery and precious-metal workers
7314	Potters and related workers
7315	Glassmakers, cutters, grinders and finishers
7316	Sign writers, decorative painters, engravers and etchers
7317	Handicraft workers in wood, basketry and related materials
7318	Handicraft workers in textile, leather and related materials
7319	Handicraft workers n.e.c.

Source: Authors, based on Eurostat. Note: n.e.c.: not elsewhere classified.

Table A.2: Correlation between the main variables, for the three main models (all regions, urban regions, rural regions)

Baseline – all regions	*Patents _employ*	*Trademarks _employ*	*Creative _sh*	*Human Capital_sh*	*Small Size_sh*	*High_tech_ service_sh*
trademarks_employ	0.559***					
Creative_sh	0.398***	0.387***				
HumanCapital_sh	0.382***	0.437***	0.609***			
SmallSize_sh	-0.166***	0.007	-0.246***	-0.242***		
High_tech_service_sh	0.349***	0.395***	0.642***	0.700***	-0.274***	
High_Tech_manuf_sh	0.169***	-0.099***	-0.214***	-0.283***	-0.277***	-0.209***

urban	*Patents _employ*	*Trademarks _employ*	*Creative _sh*	*Human Capital_sh*	*Small Size_sh*	*High_tech _service_sh*
trademarks_employ	0.575***					
Creative_sh	0.362***	0.251***				
HumanCapital_sh	0.340***	0.414***	0.537***			
SmallSize_sh	-0.288***	0.036	-0.443***	-0.257***		
High_tech_service_sh	0.393***	0.260***	0.622***	0.662***	-0.408***	
High_Tech_manuf_sh	0.046	-0.230***	-0.195***	-0.264***	-0.172***	-0.243***

rural	*Patents _employ*	*Trademarks _employ*	*Creative _sh*	*Human Capital_sh*	*Small Size_sh*	*High_tech _service_sh*
trademarks_employ	0.649***					
Creative_sh	0.278***	0.328***				
HumanCapital_sh	0.413***	0.325***	0.496***			
SmallSize_sh	-0.089*	0.051	-0.154***	-0.162***		
High_tech_service_sh	0.368***	0.369***	0.550***	0.627***	-0.091*	
High_Tech_manuf_sh	0.048	-0.070*	-0.189***	-0.315***	-0.336***	-0.156***

Note: Computed correlation used Pearson-method with listwise-deletion.

Appendix B: Robustness checks: IV strategy

The Pantheon database identifies 101 different categories, some of which rather generic (e.g. “celebrity” or “inspiration”) while other very specific (“rugby player”, “youtuber”, “snooker”). We selected relevant categories to align with our list of creative occupations, see Table B.1. This matching is not perfect, for different reasons, including the fact that the Pantheon list does not rely on current occupation categories and the fact that occupations in the 19th century are not comparable to current occupations. While some categories in the Pantheon database have a direct match with the ISCO classification (e.g. architect), others are likely to belong to multiple ISCO codes (e.g. designer, computer scientist).

Table B.1: List of 3-digit ISCO-08 codes and the corresponding occupations selected from the Pantheon database.

ISCO Code	Pantheon categories selected
216 - Architects, planners, surveyors and designers	Architect, geographer, designer
235 - Other teaching professionals	Philosopher, historian, coach, computer scientist
262 - Librarians, archivists and curators	Public worker, critic
264 - Authors, journalists and linguists	Writer, linguist, critic, journalist
265 - Creative and performing artists	Composer, musician, painter, magician, comedian, comic artist, actor, artist, conductor, dancer, producer, film director, presenter, sculptor
343 - Artistic, cultural and culinary associate professionals	Photographer, chef, designer, critic, game designer, fashion designer
352 - Telecommunications and broadcasting technicians	Computer scientist, engineer
441 - Other clerical support workers	Public worker, lawyer
731 - Handicraft workers	Chemist, engineer, businessperson

Table B.2: First stage regressions

	1st Stage - All regions	1st Stage - Rural	1st Stage - Urban
sh_bc × t_lag_eu_csh	5.309***	4.836***	6.743***
	(0.724)	(1.091)	(1.402)
lag_HumanCapital_sh	0.045***	0.036**	0.085***
	(0.011)	(0.015)	(0.023)
lag_SmallSize_sh	-0.075***	-0.114***	-0.076***
	(0.005)	(0.007)	(0.010)
lag_High_tech_service_sh	0.233***	0.260***	0.303***
	(0.054)	(0.091)	(0.089)
lag_High_tech_manuf_sh	0.044	-0.002	0.182**
	(0.029)	(0.039)	(0.074)
Num.Obs.	1680	718	502
R2 Adj.	0.868	0.789	0.888
R2 Within Adj.	0.198	0.345	0.209
Region FE	X	X	X
Year FE	X	X	X
F-test 1st St.	53.77	19.65	23.12

Note: Coefficients are significant at *p < 0.10; **p < 0.05; ***p < 0.01 level. Standard error in parentheses.